

ポスター会場（1日目） | 特別セッション：S22. 情報科学との融合による地震研究の加速

📅 2025年10月20日(月) 17:15 ~ 19:00 📍 P22会場 (502+503)(502+503)

[P22] 情報科学との融合による地震研究の加速**[P22-04] Deep-learning-based Framework for Fault-specific Seismic
Waveform Generation: From Small to Large Events**

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Traditional physics-based methods for seismic waveform generation face problems of modeling complex velocity structures and nonlinear propagation. To address such problems, deep learning related frameworks are widely proposed. This study proposes a three-stage deep learning framework using the NIED K-NET dataset to generate realistic seismic waveforms. As this study focus on the Japan Trench, NIED K-NET dataset just provides rich records for this fault with numerous observation points located in the Miyagi Prefecture.

In detail, the proposed architecture will first predict phase arrival time using a deep neural network, then generate seismic waveforms under specific conditions using conditional generative neural network, and finally transfer small-event focused model to generate large events samples. The training experiments utilize an NVIDIA A100-SXM4-80GB GPU, ensuring efficient processing of initial datasets.

In this study, small events are defined as those with magnitudes between 3.5 and 5.5, while large events exceed magnitude 6.5. In this study, all the three components of input waveforms are used for the model training. The initial waveforms are recorded at 100Hz and are uniformly downsampled to 1000 points and preprocessed under bandpass filtering.

In Stage 1, a neural network predicts the arrival times of P and S waves using key earthquake parameters, including JMA magnitude, hypocentral distance, and path-related propagation factors. The PhaseNet framework is used to singly annotate the phase information of initial data. After the convergence, the model will have the ability of inferring arrival times for even unseen data, enabling the generation of waveforms without extra known labels of phase information.

In Stage 2, a Generative Adversarial Network (GAN) is employed to generate seismic waveforms. The inputs of the generator of whole GAN model consist of a random noise / Seismic conditions (JMA magnitude, hypocentral distance, and path-related propagation factors) / Phase conditions (P and S arrival times) predicted from Stage 1. This Stage also uses supervised training and real seismic waveforms serve as ground-truth targets. An additional physics-informed loss function is introduced in order to improve physical plausibility. The total generator loss is a weighted combination of standard adversarial GAN loss and this additional physics-informed loss function, controlled via specific hyperparameters. While the total discriminator loss is a simple combination of standard adversarial loss and gradient penalty or GP to stabilize convergence in the model training. Different experiments are conducted showing that the combination of Standard adversarial GAN loss and physics-informed loss can enhance the finally output qualities

although the physics-informed loss may interface with the whole adversarial learning. In Stage 3, the focus shifts to the process of waveform generation from small to large events. The original idea is derived from the strategy of considering calculate a convolution between a small event and a source time function (STF) in order to approximate a large event in a single simulation, which is also called the classical Empirical Green's Function Method. In detail, a small-event-targeted model (Model A) is trained on small earthquake data. Then, using the output of Model A, another model which is large-event-targeted model (Model B) is trained. The supervised labels in the training process of Model B come from large earthquake data. In this process, Model B gradually learns the deconvolution-like mapping to catch the distribution of STF in this transferring process in order to map the small event data to large data.

The whole process of transferring small events to large events in the generation process uses the real samples as the Ground Truth. Similar evaluations are processed confirming the effectiveness of this process.

In summary, in this research, a multi-stage deep learning framework using the NIED K-NET dataset to generate realistic seismic waveforms is applied. By considering the prediction of phase information, the training of generative adversarial network model, the integrated physics-informed loss functions, the whole framework shows a good performance on earthquake waveforms generation.